

Predicting the Extent of Late Seasonal Wildfires in Washington Using the Correlation Between  
the Standardized Precipitation Index and Burned Area Data

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### Abstract

The amount of land burned every year in Washington has increased about ten times over the last half century making the need for improved detection and identification of trends linked to wildfires increasingly important. This project used the Standardized Precipitation Indices (SPIs) which identify periods of extreme dryness and wetness, and a Pearson Correlation test to correlate SPIs with burned area data in Washington. Monthly precipitation data in millimeters for Washington was gathered from 1948-2019 and RStudio was used to calculate r correlation values between transformed wildfire burned area data and 5 SPI indices from 1 month to 24-month time intervals formulated using the raw precipitation data. The Pearson correlation test between the two variables showed a significant correlation with  $p < 0.05$  for 18 monthly SPI indices out of the 60 total monthly indices. The strongest correlation before the month of August was found in July for the SPI12 index with p value of 0.01012 and r value of -0.5121854. The correlation is a significant negative association because a lower SPI value corresponds to extreme periods of dryness which in turn causes increased spread of fires and acres burned. The following equation was made for a spread coefficient to predict the extent of late seasonal wildfires using the SPI12July and wind speed;  $S = -0.9149 * SPI12July + 0.0105 * WS + 4.7803$ . The coefficient can be computed using real time data to help predict the extent of late large seasonal wildfires, such as the Pearl Hill or Okanogan Complex fires.

### Introduction

This research project will be able to explain trends in previous decade wildfire data using the SPI-Wildfire correlation which is important as it can be further used to create an equation to map the spread of late seasonal wildfires. Climate scenarios estimate a significant increase in forest fire danger and total burned area in the Mediterranean and North American countries with a prediction of 66% or greater increase in total burned area (Bedia et al., 2014). The area burned due to wildfires has nearly doubled over the last forty years in the US and Washington. Drought indicators have been gaining use globally to predict the presence of meteorological droughts and as a tool to help predict other climate change and drought induced events such as wildfires. The Standardized Precipitation (SPI) Index is a specific drought indicator that characterizes meteorological droughts over timescales of 1

to 24 months. The purpose of the research is to establish a correlation between the Standardized Precipitation Index for different timescales and wildfire burned area data in Washington. A negative correlation is expected for certain time scales as a lower SPI value corresponds to extended periods of dryness. These periods of dryness cause reduced soil and fuel moisture which increases the spread of forest fires.

### Materials

The materials for this research are the unchanged variables, the wildfire burned area data and precipitation data. The wildfire burned area is for Washington for the last 20 years and is in hectares. The precipitation data includes monthly and season precipitation data for the last 25 years.

### Methodology

With the local precipitation data SPI indices can be formulated by using the frequencies of different amounts of precipitations to create a probability density function for the precipitation data. This can be done for periods of 1, 2, 3, 6, and 12 months. Using the density function a cumulative probability can be calculated for specific amounts of precipitation. An inverse gaussian normal distribution which is a normal variance-mean mixture that uses an inverse Gaussian distribution as the mixing density, is done on the cumulative probability to get the SPI indices (Figure 1). The wildfire burned area data was modified using moving averages taken from removing multi-annual trends not related to drought. The length of moving averages was determined by the months of the data and the new log burned area data was calculated by subtracting log of observed data minus log of the moving average data over the log of the moving average data (Figure 2). For each month of the SPI and the log burned area data a Pearson correlation coefficient can be calculated by dividing the sum of all the deviations from the average over the square root of the sums for the data points deviation from average for each variable. Figure 1 shows an example of a graph of the Pearson correlation coefficient for each month for the SPI1 index.

Figure 1 An Example Graph of SPI Indices plotted since 1948 for SPI1

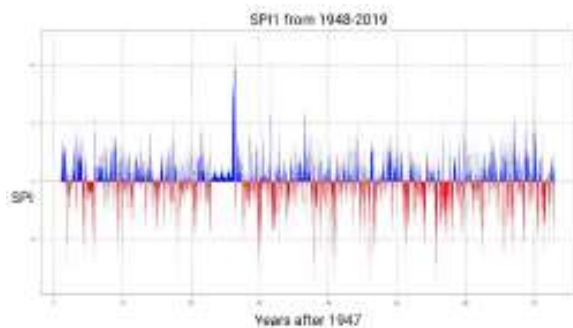
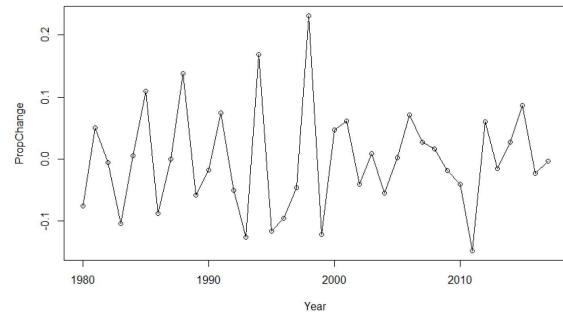


Figure 2 Proportional Change for Log Burned Area Data

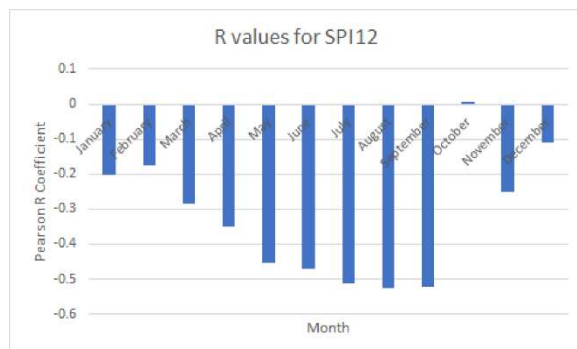


## Discussion and Results

The Pearson correlation test between the two variables showed a significant correlation with  $p < 0.05$  for 18 monthly SPI indices in the SPI1, 3, 6, 12 and 24 indices. The strongest correlations were found in the July, August, and September monthly SPIs for SPI12 with  $p$  values of 0.007385, 0.007385, and 0.01012 and  $r$  values of -0.5248249, -0.5237837, and -0.5121854 (Figure 3). The SPI6 and SPI12 had the most months with significant negative correlations. Using the correlation between the SPI12 index for July and the burned area data an equation was created to estimate the spread of late seasonal wildfires in August and September. A multiple regression model with the data for the spread of large seasonal wildfires in our state's history was used to create an equation. The equation computes the spread coefficient using the SPI12 July value along with another important factor, wind speed which estimates the maximum spread of late seasonal wildfires.  $S = -0.9149 * \text{SPI12July} + 0.0105 * \text{WS} + 4.7803$  (\*S = spread coefficient, WS = wind speed in mph). The spread coefficient equation can be used to predict the spread of large season wildfires or mini fires that converge to form large wildfires. For example, using the 2015 and 2020 SPI12 July

values, along with real time wind speed, the spread coefficient can be calculated for those fires which would've been able to predict and possibly prevent the spread of the mini fires that converged and caused those larger wildfires. The spread coefficient value can further be adjusted using the presence of topography, such as slopes or rivers. Working with the state fire marshals and the Washington State Department of Natural Resources can lead to learning about their warning system and prediction tools for the spread of fires. There is also a possibility of integrating the Standardized Precipitation Index into our state's early warning and prevention system for the spread of large late seasonal wildfires.

Figure 3 R values for the monthly SPI12 indices



## References

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### Appendices, Tables, and Figures

Figure 1 An Example Graph of SPI Indices plotted since 1948 for SPI1

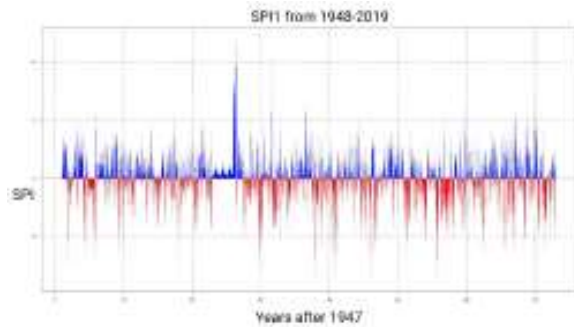


Figure 2 Proportional Change for Log Burned Area Data

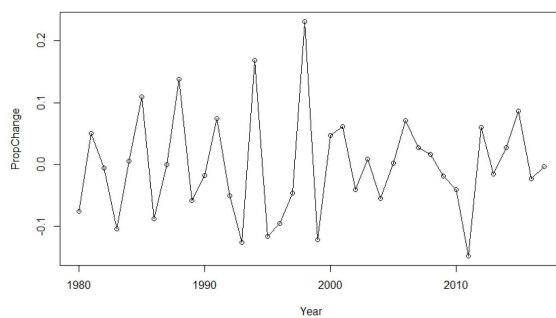


Figure 3 R values for the monthly SPI12 indices

